Analysis of Anisotropic Blind Image Quality Assessment

Submitted By

Abhishek Maddheshiya

Department of Electrical Engineering
National Institute of Technology, Rourkela
Rourkela-769008, Odisha, INDIA

May 2014

Analysis of Anisotropic Blind Image Quality Assessment

A thesis submitted in partial fulfillment of the
requirements for the degree of

Master of Technology

in

Control and Automation

by

Abhishek Maddheshiya

(Roll-211EE3338)

Under the Guidance of

Prof. Supratim Gupta

Department of Electrical Engineering

National Institute of Technology, Rourkela

Rourkela-769008, Odisha, INDIA

Department of Electrical Engineering
National Institute of Technology, Rourkela

C E R T I F I C A T E

This is to certify that the thesis entitled ***"Analysis of Anisotropic Blind Image Quality Assessment"*** *by* ***Mr. Abhishek Maddheshiya****, submitted to the National Institute of Technology, Rourkela for the award of Master of Technology in Electrical Engineering, is a record of bonafide research work carried out by him in the Department of Electrical Engineering , under my supervision. I believe that this thesis fulfills part of the requirements for the award of degree of Master of Technology. The results embodied in the thesis have not been submitted for the award of any other degree elsewhere.*

Prof. Supratim Gupta

Place: Rourkela
Date:

Dedicated to My Loving Parents, my brother Abhinav and my sister Shivangi

Acknowledgements

First and foremost, I am truly indebted to my supervisor Professor Supratim Gupta for his inspiration, excellent guidance and unwavering confidence through my study, without which this thesis would not be in its present form. I also thank him for his gracious encouragement throughout the work.

I express my gratitude to professors of my specialization, Dr. Sandip Ghosh, Dr. Susovan Samanta, Dr. Subojit Ghosh and Dr. S. Das, for their advise and care. I am also very much obliged to Head of Department of Electrical Engineering, NIT Rourkela for providing all the possible facilities towards this work.

I would like to thank Susant Panigrahi(PhD Scholar), Vipin Kamble, Susant Sawant, Sanjit Dhali, and K. Ramprabhakar at Embedded System and Real Time Laboratory, NIT Rourkela, for their enjoyable and helpful company.

My wholehearted gratitude to my parents, S. K. Gupta and Heera Gupta and my siblings Abhinav and Shivangi for their encouragement and support.

Abhishek Maddheshiya

Rourkela, May 2014

Abstract

Understanding quality of an image is a challenging task in absence of good quality reference image in many applications. In degraded image it is often assume that structure of image remains same so the objective of Blind Image Quality Assessment (BIQI) is to detect the structural degradation which is orientation dependent so blind quality of an image can be analyzed through anisotropic measure of an image. This thesis analyzes one of such Blind Image Quality Index (BIQI) measure like Anisotropic Blind Quality Index (ABQI). ABQI is measured by calculating standard deviation using Renyi entropy and directional pseudo wigner distribution. A standard database, Laboratory for Image & Video Engineering (LIVE) database is used to analyse the ABQI algorithm. The algorithm is validated by Spearman and Pearson correlation coefficients. The result provides a way of identifying best quality and noise free images from other degraded versions, allowing an automatic and non-reference classification of images according to their relative quality. It is also shown that the anisotropic measure is well correlated with classical reference metrics such as the Structural Similarity Index Measure (SSIM).

Contents

List of Abbreviations

Abbreviation	Description
1D	One Dimension
2D	Two Dimension
BIQI	Blind Image Quality Index
ABQI	Anisotropic Blind Quality Index
SSIM	Structural Similarity Index Measure
PSNR	Peak Signal to Noise Ratio
IQA	Image Quality Assessment
FR	Full Reference
RR	Reduced Reference
NR	No Reference
PWD	Pseudo Wigner Distribution
PSF	Point Spread Function
LCC	Linear(Pearson's) Correlation Coefficient
RCC	Rank(Spearman's) Correlation Coefficient
WN	White Noise
FF	Fast Fading
LIVE	Laboratory for Image and Video Engineering
MATLAB	MATrix LABoratory

List of Figures

Chapter 1

Introduction

1.1 Background

Image quality basically refers as the amount of degradation present in an image. Digital images undergo various types of distortion in process of acquisition, processing, storage, compression and reproduction. This causes certain type of degradation in the quality of an image. An image of high quality is always desirable but quality of an image cannot be concluded by brightness, contrast or sharpness. A sharp image can also have noise degradation in it. Thus there is a need of standardized method for the evaluation of the image quality in the presence of any type of degradation which can affect the image. Quality assessment using human eye is considered to be an authentic quality assessment of an image. But, assessing quality of an image using human eye requires subjective analysis of the test image. In subjective analysis image quality is decided by showing test image to certain number of observer under same environment and surroundings and then asked to give quality score for the test image. Then average of their quality score gives the final quality score of the object. Thus, using subjective analysis is avoided as it requires time, money and it is also highly inconvenient. So an automated system or algorithm is required which can approximately response like a human eye to replace this highly cumbersome process. The quality assessment algorithm will give the quality score for the image under observation and by that score we can conclude the quality of an image thereby avoiding any subjective analysis. Human eye can effortlessly decide the quality of a degraded image if the reference image is not present, but this task is rather a challenging task from a computational point of view. There are many algorithms developed to give a quality index for the image quality analysis. These QA algorithms can be categorized into following three parts-

1. Full reference image quality assessment (FR-IQA)
2. Reduced reference image quality assessment (RR-IQA)
3. No reference image quality assessment (NR-IQA)

In Full Reference Image Quality Assessment (FR-IQA), algorithm needs a reference or undistorted image to compare the test image for assessing its quality against that reference image. The quality score is decided by comparing the test image with the reference image, and depending upon the extent of distortion, the quality score of the test image is given. In case, if the reference image may not be available to the image quality assessment algorithm then it will act as a drawback for the algorithm as reference image is required to evaluate the quality of the test image.

In Reduced reference image quality assessment (RR-IQA) algorithms [1], the reference image is only partially available, in the form of a set of extracted features made available as side information in order to evaluate the quality of the distorted image. No reference image quality assessment (NR-IQA) algorithms give the quality score just by processing the test image. The reference image or any training images is not required hence it is also called Blind IQA. Though FR IQA provides a useful and effective way to analyze quality variations, in many cases there is non availability of the reference image.

In degraded image it is often assume that structure of image remains same so the objective of Blind Image Quality Assessment (BIQA) is to detect the structural degradation which is orientation dependent, so blind quality of an image can be analysed through anisotropic measure of an image. This thesis analyses one of Blind Image Quality Index (BIQI) measure like Anisotropic Blind Quality Index (ABQI).

As natural images have different directional pattern. The directional content in the image varies from images to images thus common directional pattern for natural scenes cannot be determined [2]. Anisotropy is the property of being directional dependent. It is assumed that the image degradation causes the change in the image directional information therefore because of having a directionally dependent property; anisotropy is reduced if degradation is increased in the image. ABQI is measured by calculating standard deviation using Renyi entropy and directional pseudo Wigner distribution.

1.2 Literature Review and Discussion

Humans decide image quality by seeing the image through eye. Image quality decided by image perception is different from person to person. An algorithm or system which can evaluate the quality of an image can remove the discrepancy of difference in perception.

The full reference algorithms like PSNR [3] & SSIM [4] provides a way to estimate the quality of an image but these algorithms need an original image with which the distorted image can compared to calculate the quality of image. These algorithms give the amount by which the distorted image differs from the original image. But the need of original image limits the use of these algorithms. So research work is being carried out to develop an algorithm which can evaluate the quality of an image without the need of reference image.

Different techniques have been proposed in the literature for assessing image quality when the reference image is not available. Gabarda *et al.* [5] describe a methodology to evaluate the quality of the image when reference image is not available. This method which is used in this thesis is inspired from the fact that anisotropy can play an important role in analysis of the image quality. The generalized Renyi entropy and the normalized Wigner distribution [6] is use for calculating the variance of the expected entropy of a given image which gives the pixel wise entropy values depending upon the set of predefined directions, and this calculated variance is taken as anisotropic indicator for the assessment of image quality. In this paper the anisotropic measure is correlated with full reference quality assessment metric such as peak signal to noise ratio. In the paper it is suggested that ABQI can effectively be used to assess the quality of the image and also compare the performance of this index using peak signal-to-noise ratio (PSNR). However they have not implemented their index on several types of distortions. Also as they have tested the methodology described in their paper with peak signal to noise ratio (PSNR) as the full reference quality metric but PSNR of an image is not a promising metric for quality evaluation [7]. Also the PSNR values are not consistent with the human visual system as studied in the paper [7]. Z. Wang *et al.* [4] considered structural pattern to quantify the similarity between two images, therefore Structural Similarity Index Measure (SSIM) is far better than PSNR when used as an image quality assessment metric.

[4] demonstrates the use of SSIM as full reference image quality assessment index through set of examples as well as comparison to subjective methods of the image quality evaluation. In this paper they developed SSIM that compares local pattern of pixel intensities that have been normalized for luminance and contrast. They tested their result on images compressed with JPEG and JPEG2K.

1.3 Motivation

Existing image quality assessment algorithms provide quality scores which are somewhat close to actual quality of that image but not the exact quality. Also the developed no-reference image quality assessments are distortion specific but an algorithm should be generalized and should work for all type of distortions. A new no-reference image quality assessment algorithm need to be developed which can overcome such problem. So there is a need of developing a blind quality index which should be tested on standard platform and the methodology should be compared with efficient full reference image quality assessment metric.

1.4 Objective

The objectives of the thesis are:

1. Analysis of Anisotropic Blind Image Quality Index method.
2. Implementing ABQI algorithm on LIVE image database.
3. Analysis of performance of algorithm by comparing it with standard full reference image quality assessment metric, SSIM.

1.5 Contribution of Thesis

The following are the salient contributions of the thesis.

1. The Blind image quality index algorithm is studied.
2. Anisotropic Blind Quality Index algorithm is validated on a standard database i.e. Laboratory for Image & Video Engineering (LIVE) [8] using Spearman & Pearson correlation.
3. Type of distortions on which ABQI algorithm will perform better in assessing image quality is concluded on the basis of experimental results.

1.6 Thesis Organization

This thesis is organized as follows -

- Chapter 1 gives an introduction to blind image quality assessment. This chapter introduces that anisotropy can be taken as measure for assessing the image quality.
- Chapter 2 describes about the anisotropic blind quality index. This chapter analyses Blind Image Quality Index (BIQI) measure like Anisotropic Blind Quality Index (ABQI) and discussed that how ABQI is measured by

calculating standard deviation using Renyi entropy and directional pseudo Wigner distribution.

- Chapter 3 describes the performance index (SSIM) which used further to compare it with ABQI for checking the proper dependency and validity of the developed algorithm. It also describes about the correlation coefficients which was further used in experiment to measure the closeness between ABQI and SSIM indices.
- Chapter 4 describes about the image database used for the experiment. It gives the result on the extensive study on the total of 779 images of the image database which were used for experiment.
- Chapter 5 concludes the thesis.

Chapter 2

Analysis of ABQI Algorithm

2.1 No Reference Image Quality Assessment

Image quality index is the measure for estimating the amount of degradation present in an image. Several methods are available for the estimation of image quality in presence of a reference image. When a reference image is present then evaluating visual quality in comparison to the reference image is a comparatively easier and more accurate. While using FR-IQA if the reference image may not be available to the image quality assessment algorithm then it will act as a drawback for the algorithm as reference image is required to evaluate the quality of the test image. Estimating image quality when the reference image is not present is quite a typical task to be done. This type of image quality assessment when reference image is not present for analysing the visual quality is referred as No Reference Image Quality Assessment or Blind image quality assessment.

2.2 Blind Image Quality Assessment

In situation when a reference image is not present then only blind image quality assessment algorithms can be used in the image quality analysis. The blind image quality assessment method which we are focussing in this thesis is based on calculating the image anisotropy.

Natural images have different directional pattern. The directional content in the image varies from images to images thus common directional pattern for natural scenes cannot be determined. Information content in an image can be measured using a parameter called entropy. It is a measure of uncertainty. Entropy is not directionally sensitive. To show the information or amount of uncertainty in a source Shannon entropy is used. Entropy and quality of an image are both related to each other. If given image is a source, then noise is the main hindrance for considering entropy to be a quality index as noise itself is a kind of information. Thus it cannot be differentiated by information content in the image. Noise, blurring or flickering can easily be identified by the human eye or human visual system. Hence, entropy cannot be considered as a good indicator for quality assessment of an image. Thus, to avoid this situation, anisotropy is used as a measure of image quality. Entropy is somehow related to anisotropy which has directional sensitivity. Anisotropy is the property of being directional dependent.

In natural images, directional content varies from image to image, thereby no common pattern exist for directional content with the variation in scene composition. While developing the ABQI method it is assumed that the image degradation causes the change in the image directional information therefore because of having a directionally dependent property, anisotropy is reduced if degradation is increased in the image.

Keil *et al.* [9] done some experiment regarding sharing of energy in natural images in spatial frequency domain and while calculating the frequency content of an image using a directional PWD they observed that entropic measures such as Renyi entropy can be considered as a suitable tool in analysis of image anisotropic measure.

Natural images comprise of edges and textures and from image to image there exist texture diversity. This edges and texture diversity is the cause of image anisotropy. Using spatial frequency content of an image the entropy can be calculated locally. Thus, entropic measure is connected to anisotropy.

According to the anisotropy of the images, entropy measures with different orientation provide different values of entropy as entropy measures information. Natural scene can be taken as random process which implies that anisotropy will likely statistically canceled out if their average is taken and their size is assumed to be infinite. But, in image processing techniques only size limited images are processed. Due to this size limitation of the images anisotropy comes into picture. A slight variation in the anisotropy is relevant when entropy is taken in account at pixel level. These entropy variations are basically due to the big influence of edges to the entropy values. Edges are responsible for the important variations on entropy of an image at pixel level.

The basic mathematical explanation of the method is explained in next section.

2.3 Renyi Entropy

The information content of set of data is measured by entropy. An image can be described as information carrying 2-D array. Changes in entropy orientation gives changes in the content of information this implies that in anisotropic way, the information can be stored. Specifically when there is any kind of information in the orientation then entropy is very important property to consider. To measure variation in different entropic characteristics with different types of images, directional entropy may be used. By using Renyi entropy we can achieve entropy with directional property.

Shannon and Wiener independently proposed the definition that entropy of an information source is a measure of the information content per symbol. Further, Renyi extended above notion to get general form of entropy. Various types of distributions are taken for defining Renyi entropy measures. With the help of Flandrin *et al.* [10], Williams *et al.* [11] introduces these Renyi entropy measure in time-frequency analysis. Generally, the Renyi entropy applying to a discrete space frequency distribution has the form:

$$R_\alpha = \frac{1}{1-\alpha}\log_2\left(\sum_n\sum_k P^\alpha[n,k]\right) \tag{2.1}$$

Shanon entropy can be obtained by tending $\alpha \to 1$.

$$H = -\sum_n\sum_k P_x[n,k]\log_2\left(P_x[n,k]\right) \tag{2.2}$$

Here n, k shows the spatial & frequency variables. And, $\alpha \geq 2$ are values recommend for space-frequency distribution measure [10]. Normalization is necessary for reducing a distribution to the unity signal energy, which can be done in various ways [12, 10]:

2.3.1 Signal Energy Normalization

$$RE_\alpha = \frac{1}{1-\alpha}\log_2\left(\frac{\sum_n\sum_k P_\alpha[n,k]}{\sum_n\sum_k P[n,k]}\right), \alpha \geq 2 \tag{2.3}$$

The behavior of given measure is nearly same as the un-normalized measure form, except in its magnitude. This type of normalization is essential when comparing different distributions or similar distributions if the energy is biased.

2.3.2 Volume Distribution Normalization

$$RV_3 = -\frac{1}{2}\log_2\left(\frac{\sum_n\sum_k P^3[n,k]}{\sum_n\sum_k \mid P[n,k] \mid}\right) \tag{2.4}$$

The type of normalization is applied in adaptive kernel design [11]. The logarithm is a monotonic function, but here the term within the log is just the ratio of norms $L3$ and $L1$. Hence, measure Eq.2.4 can be taken as L_3/L_1, which reduces it to the generalized form.

2.3.3 Quantum Normalization

This type of normalization is inspired by quantum mechanics by taking the spatial or spatial frequency distribution P of a given position n with a wave function and deriving its probability density function using $\overline{P}[n,k] = P[n,k]P^*[n,k]$ and then normalized it to fulfil the condition $\sum_n \sum_k \overline{P}[n,k] = 1$.

putting $\alpha = 3$ in Eq.2.1 to give-

$$\overline{R_3} = -\frac{1}{2}\log_2\left(\sum_n \sum_k \overline{P^3}[n,k]\right) \tag{2.5}$$

Considering on point wise basis:

$$\overline{R_3}[n] = -\frac{1}{2}\log_2\left(\sum_k \overline{P^3}[n,k]\right) \tag{2.6}$$

The term $\overline{P}$ in Eq.2.6 is to be normalized by $Q[n,k] = P[n,k]P^*[n,k]$ and then by $Q[n,k] = Q[n,k]/\sum_n Q[n,k]$ to fulfil the normalization criteria: $\sum_n \overline{P}[n,k] = 1$,$\forall n : 1 \leq n \leq M$; where M is data size and $-N/2 \leq k \leq N/2-1$ is the spatial window for computing the measure. This type of normalization has been particularly selected for the calculation of the normalized Renyi entropy using one dimensional pseudo Wigner distribution for given orientation angle and fixed window size.

2.4 1-D Pseudo-Wigner Distribution:

The information of spatial frequency of a test image can be obtained by the association of gray level spatial data and spatial/spatial-frequency distribution [13]. In this type of distributions, Renyi entropy has been applied specifically. The algorithm analyzed in this thesis uses Wigner distribution [2]. In this condition, by taking a small window of size N we can link a particular pixel n of an image with a vector consisting its one dimensional PWD. The three important features of the problem justifying the purpose in using a one dimensional windowed transform for a two dimensional signal are-

1. The data can positioned accordingly in any direction using 1-D PWD over a 2-D image.

2. Comparing it with the 2-D version of the PWD, the execution time is much reduced.

3. The data can be fully preserved as it is an invertible function.

Claasen *et al.* [6] proposed the approximated version of the Wigner Distribution which is given by the equation-

$$W_z[n,k] = 2 \sum_{M-N/2}^{N/2-1} z[n-m]z^*[n-m] \exp^{2i(2\pi m/N)k} \tag{2.7}$$

Here n and k depicts the time and frequency discrete variables, m is a discrete parameter for shifting. Also,$z[n]$ is a 1-D sequence of image data align in desired direction and it contains gray values of N pixels. For the expression $z[n+m]z^*[n-m]$ this equation can be treated as its Discrete Fourier transform (DFT). Where z^* represents the complex conjugate of z. Above equation is defined in the PWD's window i.e. $[-N/2, N/2-1]$ for extracting information locally. We get the total pixelwise PWD of the image by moving the window over whole image. Directional distribution can be obtained by tilting the window in desired direction. $W_z[n,k]$ with $\overline{P}[n,k]$ had been normalized and associated to each other. Now, for a discrete sequence $z[n], w_n[k]$ is measured with N data values centred at pixel position n using Eq.2.7 and fixed at each pixel position n. Quantum normalization is used to normalize the local PWD which further identify the PWD with probability distribution $\overline{P}_n$, and the Renyi entropy related with position n can be computed as

$$R_3[n] = -\frac{1}{2}\left(\sum_{k-1}^{N} \overline{P_n^3}[n,k]\right) \tag{2.8}$$

Above equation gives the entropy value $R_3[n,\theta]$ for each pixel. The expected value of this equation is calculated as

$$\overline{R}[n,\theta_s] = \sum_n R_3[n,\theta_s]/M \tag{2.9}$$

Here M depicts the size of image and $t \in [1, 2, .., T]$ where T is the number of different images taken for calculation [for making above equation more simple, t has been omitted in the right side of equation] and $\theta_s \in [\theta_1, \theta_2, ...\theta_S]$ depicts S different orientations taken to measure entropy. Six equally spaced predefined directions$(0, 30, 60, 90, 120, 150)$ has been taken for the different orientations though there so no such limit and number of direction will not affect the performance of the algorithm.

Assuming $\overline{R}[t, \theta_s]$ is the expected value of entropy for image and $t \in [1, 2, ...M]$, measured in different orientations $\theta_s \in [\theta_1, \theta_2, ...\theta_S]$. Thus, standard deviation $(\sigma(t))$ for the resulting set of values, relative to image t, can be defined as

$$\sigma(t) = \sqrt[2]{\sum_{s=1}^{S} \left(\mu_t - \overline{R}(t, \theta_s)\right)^2 / S} \tag{2.10}$$

where μ_t is the mean of the values $\overline{R}[t, \theta_s]$, as defined by the expression

$$\mu_t = \sum_{s=1}^{S} \overline{R}(t, \theta_s)/S \tag{2.11}$$

The variance (standard deviation) of these expected values has been selected as an indicator for the anisotropy of the images. Now in order to illustrate the performance of the method, a well-known image, Lena is taken of 256×256 pixels and 8 bits/pixel and processed using the method describe above. A set of 8 progressively blurred and noisy image has been generated (four blurred version and four noisy version) from original image (represented as Fig.2.1(a)). When the source image is applied to a blurring point-spread function (PSF) a set of four blurred image is generated (from Fig.2.1(b) to Fig.2.1(e)). The maximum blurring appears on the image labeled as Fig.2.1(e). Also, another set of four noisier images has been generated by adding speckle noise to the original image from (Fig.2.1(f) to Fig.2.1(i)). The maximum noise appears on the image labeled as Fig.2.1(i). This makes a set of 9 versions of the same view,

(a) (b) (c)

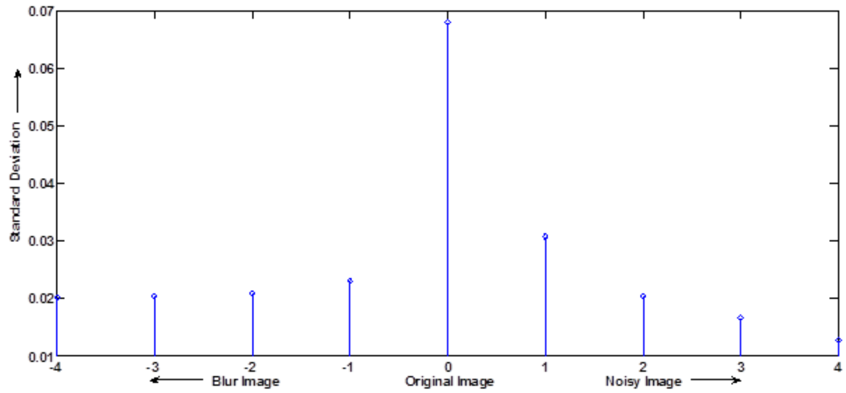
(d) (e) (f)

(g) (h) (i)

Figure 2.1: Original image(a) and corresponding blurred and noisy version of the original image

with an original image and its 8 degraded versions degraded by blur or noise with different strength.

Now, in the original image a fixed window size of $N = 8$ has been considered and orientation angle $\theta = 0^o$ is taken. Later the procedure can be extended to any no of orientations. Then, pixel wise pseudo-Wigner distribution for the image is calculated with N-pixels 1D oriented window for all the pixels of the image. Then, normalized Renyi entropy of the image is calculated for the given orientation angle of the window. This is repeated for different orientation angle $\theta = 0^o, 30^o, 60^o, 90^o, 120^o \& 150^o$ and corresponding normalized Renyi entropy related to each pixel is determined. Now, expected value of the all the calculated normalized Renyi entropy measured in directions $\theta = 0^o, 30^o, 60^o, 90^o, 120^o \& 150^o$ is calculated. From this expected value using Eq.2.10 standard deviation rela-



(a)

Figure 2.2: Plot for the Standard Deviation of an Image and its degraded blurred and noisy versions.

tive to that image is determined.

Image labeled as Fig.2.1(a) is the original image (Lena) or the reference image. And images from Fig.2.1(b) to Fig.2.1(e) are the progressively degraded blurred image versions of the original image. Images from Fig.2.1(f) to Fig.2.1(i) are the progressively degraded noisy version of the original image. From left to right, images get degraded with increasing blur or noise. Here multiplicative noise i.e. speckle noise is added to produce the degraded version of the reference image. The standard deviation of the expected values of directional Renyi entropy is calculated for each burred and noisy versions of the original image through MATLAB coding using the method studied. Now, the standard deviation value of the original and corresponding progressively blurred and noisy images is calculated and it is shown in a Fig. 2.2 with standard deviation of original image being in the middle serving as a reference image and at the left side and right side being the standard deviation of progressively blurred and noisy images respectively.

Similarly, this method is applied to different blur and noisy versions of the original image and corresponding standard deviation is calculated.

Now the plot is drawn representing standard deviation values of original or reference image along with its four blur version on left side of the original image, with extreme left being the most blurred version and on the right is four noisy version with extreme right being the most noisy version.

The shape of the curve in the plot represents the following desirable properties that:

1. Accuracy, i.e. as we got a distinct maximum for the original image.
2. Unimodality, i.e. we got a single maximum for the best quality.
3. Computationally efficient.

Thus selection of the standard deviation of the expected values of Renyi directional entropy has been empirically confirmed as a good indicator of anisotropy for natural images. Thus the standard deviation of the expected values of Renyi directional entropy is taken as index to measure non reference image quality assessment. Hence, Anisotropic Blind Quality Index (ABQI) is an algorithm to analyzes the quality of an image without the need of a reference image.

The standard deviation of Renyi directional entropy as mentioned in Eq.2.10 is compared with some standard measures such as PSNR and SSIM [4] (See Sec.3.3). An experiment is carried out on 'Lena' image and the degradation (Both in Blur and Noise) is increasing from Fig.2.1(b) to Fig.2.1(i). The comparison result of ABQI and other mentioned metrics are shown in Table.3.1.

Table 2.1: Comparison of different Image Quality measures

Lena	PSNR	SSIM	$\sigma(t)(See Eq.2.10)$
Fig.2.1(a)	–	1.0000	0.067915
Fig.2.1(b)	23.5790	0.6755	0.229680
Fig.2.1(c)	23.3435	0.6623	0.020899
Fig.2.1(d)	23.2140	0.6549	0.020281
Fig.2.1(e)	23.0352	0.6505	0.020123
Fig.2.1(f)	20.9927	0.4321	0.030611
Fig.2.1(g)	18.8657	0.3578	0.020325
Fig.2.1(h)	17.5104	0.0309	0.016566
Fig.2.1(i)	16.4568	0.2746	0.012775

2.5 Summary

This chapter describes about the anisotropic blind quality index. This chapter analyzes Blind Image Quality Index (BIQI) measure like Anisotropic Blind

Quality Index (ABQI) and discussed that how ABQI is measured by calculating standard deviation using Renyi entropy and directional pseudo Wigner distribution. The developed algorithm has been explained with all mathematical explanations. The development required use of many signal processing tools. There formulation and definition have been incorporated in the chapter.

Chapter 3

Performance Index

3.1 Full Reference Image Quality Assessment

Digital images undergo various types of distortion in process of acquisition, processing, storage, compression and reproduction. For areas where the processed images are to be perceived by human eye then subjective analysis of the processed image is required for providing the quality of an image. This might not be possible always as it requires time, money and is much inconvenient. So, we can develop an algorithm or certain measure which can approximately response like a human eye to replace this highly cumbersome process. The developed algorithm will give the quality score for the image under observation and by that score we can conclude the quality of an image thereby avoiding any subjective analysis.

There are many measures developed which provides an index for the image quality analysis. Full reference image quality assessment is one of the existing different types of image quality assessment methods. In Full Reference Image Quality Assessment (FR-IQA), algorithm needs a reference or undistorted image to compare the test image for assessing its quality against that reference image. The quality score is found out by comparing the test image with the reference image, and depending upon the extent of distortion the quality score of the test image is given. There are many FR-IQA methods exists like Structural Similarity Index Measure (SSIM), Fast SSIM and Peak Signal to Noise

Ratio (PSNR). Out of these the interest of this thesis lies in SSIM as in this thesis SSIM is taken as a standard algorithm to be compared with the developed no-reference image quality assessment index, ABQI.

3.2 Why SSIM ?

Today different type of No-Reference Image Quality Assessment algorithms exists but differentiating them that which algorithm is better is quite a typical task to be done. As one algorithm can take less computational time but may give less accurate result whereas another algorithm can take more computational time but may give more accurate results. Accuracy and computational time decides the purpose of an algorithm. So, to check the performance of the developed ABQI algorithm, it is applied on LIVE image database. LIVE database is a standard image database used to check and validate the image quality assessment algorithms by providing different sets of standard images and their corresponding distorted images. Since ABQI is a No-Reference image quality assessment algorithm hence it is required that this algorithm should be compared with some other existing standard algorithm. Therefore Structural Similarity Index Measure (SSIM) metric is used for the said purpose. SSIM is one of the Full Reference Image Quality Assessment algorithms and have a high correlation value.

3.3 SSIM

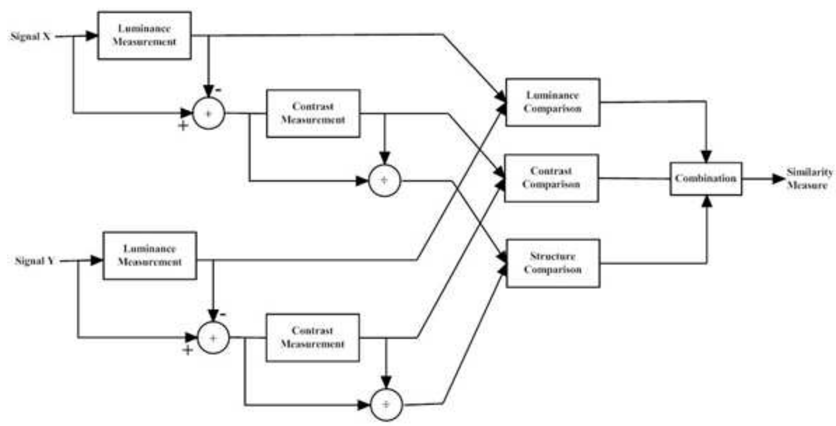
Structural Similarity Index Measure (SSIM) is one of the full reference image quality assessment methods. In full-reference image quality assessment methods, the quality of a test image is evaluated by comparing it with a reference image that is assumed to have perfect quality.

As Wang *et al.* [4] proposed that the image quality may be distorted during the processing, compression, storage and reproduction of digital image, which ultimately affects the visual quality. The objective of their research in image quality assessment is to develop quantitative measures that can automatically predict perceived image quality. Hence they come up with a measure called structural similarity index (SSIM).

The aim was to design method to measure the strength of the perceptual similarity (or difference) between the test image and reference image. SSIM is motivated from the observation that natural image signals are highly structured; meaning that the signal samples are highly dependent on themselves when they are spatially very close to each other and due to these closely spaced samples, they carries important information about the structure of the objects in the visual scene.

The luminance of the observed surface of an object is the product of the reflectance and illumination. However, the structure of an object is independent of illumination in a scene. So, to have the information about the structure of an image, it is required to separate the influence of illumination. Therefore, the structural information in an image can be defined as the attribute that represent the structure of an object in the scene. As SSIM is a full reference image quality assessment algorithm, it requires a test image to be compared from a reference image to estimate the quality of the test image. The parameters that are considered for comparison are the luminance, contrast and structure of an image. These three factors are calculated from the images and relative score is being provided to the test image. These three factors are some of the necessary factors used by the human eye to give a subjective analysis of an image. These physical factors are simulated with the use of the basic statistical parameters like mean, variance and covariance.

Fig.3.1 represent the structural similarity between two non-negative image signals X and Y, that are aligned to each other. The above system separates the task of similarity measure considering the quality of one signal to be of perfect quality, into three comparisons: luminance measurement, contrast measurement and structure measurement.



(a)

Figure 3.1: Structural similarity measurement system (SSIM)

3.3.1 Luminance Comparison

Following equation gives the statistical analysis of the luminance comparison of two images-

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \tag{3.1}$$

where $C_1 = (K_1L)^2$.

Here μ indicates the mean of the image pixel. The C_1 factor is added to provide stability to the equation in case of zero in the denominator. In the equation 3.1 the constant L defines the range of pixel intensity values in an image which is generally 255, hence it is considered constant for most of the case. As L is considered constant for most of the cases, the constant C_1 is then governed totally by the constant K_1. The constant $K_1 \ll 1$, the value is decided such that it should provide stability to the equation as well as should not dominate the comparison factor.

3.3.2 Contrast Comparison

Following equation gives the statistical analysis of the contrast comparison of two images-

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \tag{3.2}$$

where $C_2 = (K_2L)^2$

here σ indicates the standard deviation of the image pixel. The C_2 factor is added to provide stability to the equation in case of zero in the denominator. In the equation 3.2 the constant L defines the range of pixel intensity values in an image which is generally 255, hence it is considered constant for most of the case. As L is considered constant for most of the cases, the constant C_2 is then governed totally by the constant K_2. The constant $K_2 \ll$, the value is decided such that it should provide stability to the equation as well as should not dominate the comparison factor.

3.3.3 Structure Comparison

Following equation gives the statistical analysis of the structure comparison of two images-

$$s(x, y) = \frac{2\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{3.3}$$

here σ_{xy} indicates the covariance between the image pixels of two images under consideration. The constant is same as that in previous two cases. These comparison parameters are then combined together to for a unique Index called as SSIM index. The contribution of the parameters is generally taken as equal and so the resultant equation for SSIM calculation after some simplifications and assumption is

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{3.4}$$

The default values of the constants used which were defined above are- $K_1 = 0.01$

$K_2 = 0.03$

$L = 255$

Now an example is taken to illustrate the property of SSIM.

Figure 3.2: (a)Original image (SSIM=1), (b) WN degraded image (SSIM 0.5470), (c) WN degraded image (SSIM 0.4193), (d) WN degraded image (SSIM 0.3494)

In below example, standard original image 'Lena' is taken and it is then progressively degraded by adding zero mean Gaussian white noise with different variance 0.01, 0.02 and 0.03 for Fig.3.2(b), 3.2(c) and 3.2(d) respectively.

The corresponding SSIM values for the original image and its progressively degraded version are 1, 0.5470, 0.4193 and 0.3494 respectively. SSIM value for original image is 1 as it is a full reference image quality assessment metric, hence it compares the original image from itself as it is taken as the standard image 3.2(a). It is observed that corresponding SSIM values for the degraded version tends to decrease as the strength of the degradation is increased.

In this thesis SSIM is taken as a standard full reference image quality assessment algorithm which is then compared with the developed no-reference image quality assessment index, i.e. anisotropic blind image quality index. This comparison is done using Pearson and Spearman correlation coefficients to check the validity of the developed algorithm. Both the correlation coefficients are explained in next section.

3.4 Correlation Coefficients

The correlation coefficient, also called the cross-correlation coefficient, is a measure of the strength of the relationship between pairs of variables. It determines the degree to which the two variables are associated to each other. Correlation may be:

1. **positive** (i.e. there is increase in the values of one variable as the values of another variable increases)

2. **negative** (i.e. there is decrease in the values of one variable as the values of another variable increases)

Correlation is measured on a scale from -1 to 1.

Correlation value is equal to 0 represents no correlation i.e. the two variables are independent to each other.

Typically, the correlation coefficients reflect a monotone association between the variables. Correspondingly, positive correlation is said to occur when there is an increase in the values of one variable as the values of another variable increase. Perfect positive correlation occurs at correlation value equal to 1 i.e. values of one variable is changing at the same rate as that of another variable.

Negative correlation occurs when the values of one variable decrease as the values of another variable increase (or vice versa). Correlation value equal to -1 represents perfect negative correlation i.e., the values of variables are changing at the same rate but in the opposite direction. Hence, closer is the correlation value to 1 or -1, the stronger is the correlation.

In our context, performance of the developed ABQI algorithm can be validated using different correlation coefficients. Here ABQI algorithm which is a non-reference image quality assessment algorithm is compared with a full reference image quality assessment algorithm i.e. SSIM metric, using Pearson and Spearman correlation coefficients. Both the correlation coefficients are explained in next section.

3.4.1 Pearson Correlation

Pearson correlation is used to measure the strength of the linear association between two variables [14]. Pearson correlation is also called as linear correlation. It gives the correlation values between two variables which lies between '-1' & '$+1$'. Here correlation value close to '-1' indicates that the two variables have strong negative correlation and correlation value close to '$+1$' indicates that the two variables have strong negative correlation. Value equal to '0' implies that the two variables are uncorrelated or independent to each other. The Pearson correlation coefficient 'ρ' can be defined as follows [15]. Assuming that there exist two variables X and Y, each having n values like $X_1, X_2, ...X_n$, and $Y_1, Y_2, ...Y_n$, respectively, then Pearson correlation coefficient 'ρ' is

$$\rho = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})_2 \sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{3.5}$$

where the mean of X is represented by $\overline{X}$ and the mean of Y is represented by $\overline{Y}$. Thus Pearson correlation coefficient 'ρ' between two variables 'X' and 'Y' can also be given by-

$$\rho = \frac{cov(X, Y)}{\sigma_X \sigma_Y} \tag{3.6}$$

where σ_X and σ_Y are the standard deviations, and $cov(X, Y)$ is the covariance.

3.4.2 Spearman Correlation

Spearman Correlation is also called as rank correlation. In certain cases where there is non linear association between two variables, the relationship can be converted into a linear relationship by using ranks of the items in spite of its actual value. Thus ranks itself can be taken as new variables instead of data values[16]. Thus correlation between these two variables can be calculated as there is a linear relationship between these two variables. Spearman is a rank based correlation in which we take rank of the variable in the set to calculate the correlation rather than taking the actual value [15]. The rank correlation coefficient 'ρ_s' is given by-

$$\rho_s = \frac{\sum_{i=1}^{n}(rankX_i - \overline{r}ankX)(Y_i - \overline{r}ankY)}{\sqrt{\sum_{i=1}^{n}(rankX_i - \overline{r}ankX)^2 \sum_{i=1}^{n}(rankY_i - \overline{r}ankY)^2}} \tag{3.7}$$

Where $-1 \leq \rho_s \leq 1$. $\rho_s > 0$, shows positive monotonic association between two variables $\rho_s < 0$, shows negative monotonic association between two variables $\rho_s = 0$, shows there is no association between two variables. For values of $|\rho_s| = 1$ the two functions are in perfect monotonic relationship with each other. These are the ideal values we require for testing of the developed algorithm.

The performance of the developed ABQI algorithm can be validated using different correlation coefficients. In this thesis, the performance of ABQI (which is a non-reference image quality index) is compared with SSIM (which is a standard full reference image quality parameter), using Pearson and Spearman correlation coefficients.

For test purpose ABQI algorithm is applied on a well-known standard image 'Lena'. Firstly, standard image 'Lena' is taken as a reference image and it is then processed to introduced Gaussian white noise in it by varying variance and taking mean equal to zero. Likewise seven degraded images of original image (represented as Fig.3.3(a)) are produced (from Fig.3.3(b) to Fig.3.3(h)). The maximum noise appears on the image labeled as Fig.3.3(a). This makes a set of 8 versions of the same view, with an original image and its 7 degraded versions degraded by white noise with different strength.

ABQI values for seven degraded versions are calculated using ABQI algorithm and SSIM values for seven degraded version is calculated taking original image as reference image for the comparison. The image is degraded by adding Gaussian white noise to it. Then to check the correlation between ABQI values

Figure 3.3: Original Image (a) and progressively degraded noisy versions of the original image

and SSIM values Pearson and Spearman correlation is applied. Pearson Correlation Coefficient and Spearman Correlation Coefficient values are calculated taking ABQI and SSIM values (for the degraded images of the original image) as their two variables.

Table 3.1: Comparison of different Image Quality measures

Degradation Strength(Gaussian White Noise $\mu = 0$)	ABQI	SSIM	LCC	RCC
Var = 0.01	0.0024	0.7894		
Var = 0.02	0.0013	0.6796		
Var = 0.03	0.0012	0.6052		
Var = 0.04	0.0089	0.5556	0.9545	0.9643
Var = 0.05	0.0054	0.5763		
Var = 0.06	0.0084	0.4842		
Var = 0.07	0.0035	0.4569		

Pearson Correlation Coefficient and Spearman Correlation Coefficient values 0.9545 and 0.9643 respectively suggest that the developed index measure i.e. ABQI is closely related to the SSIM index. These values give the monotonic accuracy of the ABQI index.

3.5 Box Plot

The box plot is a graphical representation of data that shows a data set's lowest value, highest value, median value, and the size of the first and third quartile. The box plot is an alternative to histograms when small data sets are analysed. Because of the small size of a box plot, it is easy to display and compare several box plots in a small space. A box plot is a good alternative or complement to a histogram and is usually better for showing several simultaneous comparisons.

In Box plot we get to visually see the extent of the variation of the data-points about its median. The box plot is in the form of a rectangular figure with a vertical line passing through it. The horizontal edges of this box represent the 25th and 75th percentiles of the data set. The line passing through the box is called as whiskers; the end points of the whiskers represent the extreme points of data-set excluding any outliers if present. The outliers are the values which are about twice the standard deviation from the mean of the dataset. The box-plot also indicates the median of the set, which is indicated by a horizontal line which is indicated inside the box.

3.6 Summary

This chapter describes the performance index (SSIM) which was used further to compare it with ABQI for checking the proper dependency and validity of the developed algorithm. It also describes about the correlation coefficients and box plot which was further used in experiment to measure the closeness between ABQI and SSIM indices.

Chapter 4

Experimental results and discussions

This chapter will be dealing with the results of the developed Anisotropic Blind Quality Index (ABQI) algorithm applied on LIVE image database. As SSIM is a standard metric for image quality assessment therefore this index is used to measure the efficiency of the ABQI for the assessment of the image quality to quantify the quality of the image. The results are acquired with the help of MATLAB platform. Some of the toolbox in MATLAB like, image processing toolbox, statistical toolbox, signal processing toolbox etc. was used. Results and discussions regarding the experiment are given in following sections.

4.1 Image database

An image processing database is a database full of images and image processing algorithms that are used by researchers to discover and test new processing methods or algorithm. Different types of image degradations are possible like noisy image, blurry image etc., so the database must include a large variety of images. All the images are included in the database, so users can apply processing methods over the images in batches to measure the processing effects, which is much faster than processing the images in other programs. The images of the database are generally used for research. For accurate test results, the image processing database must comprises of different types of images.

Along with providing researchers with a lot of images to work with, an image processing database also helps in applying the image processing. Since all the images are in a database, so if any application is required to be done it can normally be applied in batches to the images. This is much faster than most photo software, which can normally apply changes to one image at a time.

Image database have been developed to check and verify the authenticity of an algorithm which provide the standard for the validation of the developed algorithm. The developers of the image database have made the image database as an open source. Each image database consists of set of images which act as a reference image and image database also comprises of the distorted version of the same set of provided reference images. Each database consist differently distorted version. The distortion of the reference image varies in type of distortion and level of distortion of the reference image. Each database comprises of set of reference images in separate folder and different type of distorted images in different folder grouped according to their type and level of distortion. Level of distortion for each image is also mentioned in concerned folder.

From these databases one can validate their developed algorithm by applying their algorithm on image database and use this database as a standard to conclude any result of their observation. Mostly all databases include all important types of distortion.

4.2 Why LIVE Database?

Today different type of No-Reference Image Quality Assessment algorithms exists but differentiating them that which algorithm is better is quite a typical task to be done. As one algorithm can take less computational time but may give less accurate result whereas another algorithm can take more computational time but may give more accurate results. Accuracy and computational time decides the purpose of an algorithm. The trade-off between accuracy and computational time may exist in deriving an algorithm so researchers need to take care of that. So, to check the performance of the developed ABQI algorithm, it is applied on LIVE image database.

Laboratory for Image and Video Engineering (LIVE) database is a standard image database used to check and validate the image quality assessment algorithms by providing different sets of standard images and their corresponding distorted images.

The LIVE database [8] had been developed at the University of Texas at Austin, USA, and it contains reference images and distorted images in 24-bpp color BMP format at different image resolutions ranging from 634×438 pixels to 768×512 pixels. It comprises a set of reference images incorporated in a separate folder along with different folders of different type of distortion with different distorting level. There are 29 different reference images used in this database. Each reference image is distorted by 5 different types of distortion and each type of distortion is degraded with different degraded level. Hence total 779 images are available in this database. The different type of distortion used here are:

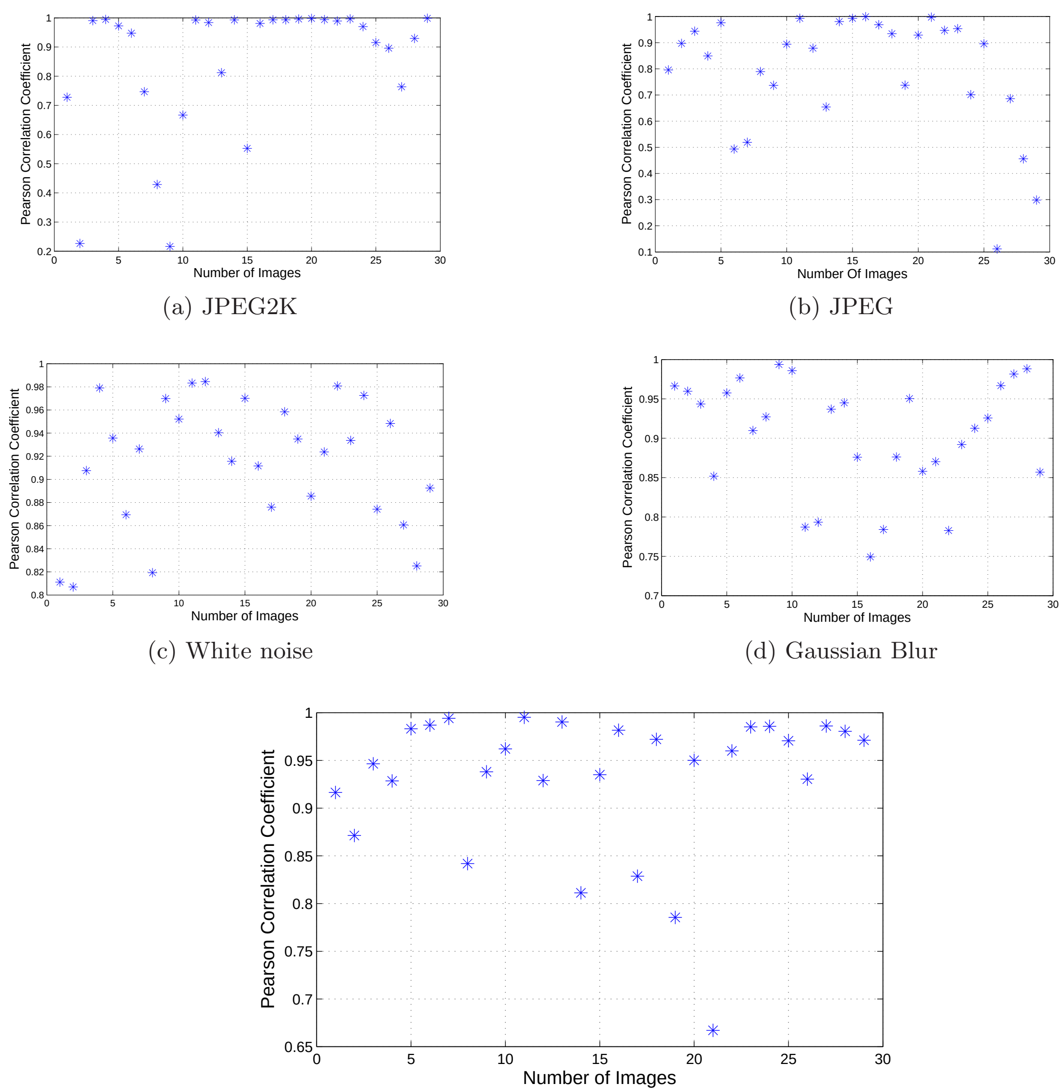
- JPEG2000 compression (169 distorted images)
- JPEG compression (175 distorted images)
- White Noise (145 distorted images)
- Gaussian Blur (145 distorted images)
- Fast Fading (145 distorted images)

Anisotropic Blind Quality Index (ABQI) algorithm was applied on LIVE image database and results are discussed in the following section.

4.3 Results

This section will illustrates the result obtained using comparison parameters i.e. Pearson and Spearman correlation coefficients (explained in section 3.4).

Though there are different blind image quality assessment indices available in the literatures, in this thesis we have considered the newly proposed direction based image quality assessment known as Anisotropic Blind Quality Index. S. Gabarda *et al.* [5] argued that this index can effectively be used to assess the fidelity and quality of image and also compare the performance of this index with some classical full reference metrics such as peak signal-to-noise ratio. However in this thesis we have considered a more capable and efficient image quality index i.e. SSIM to measure the performance of ABQI.



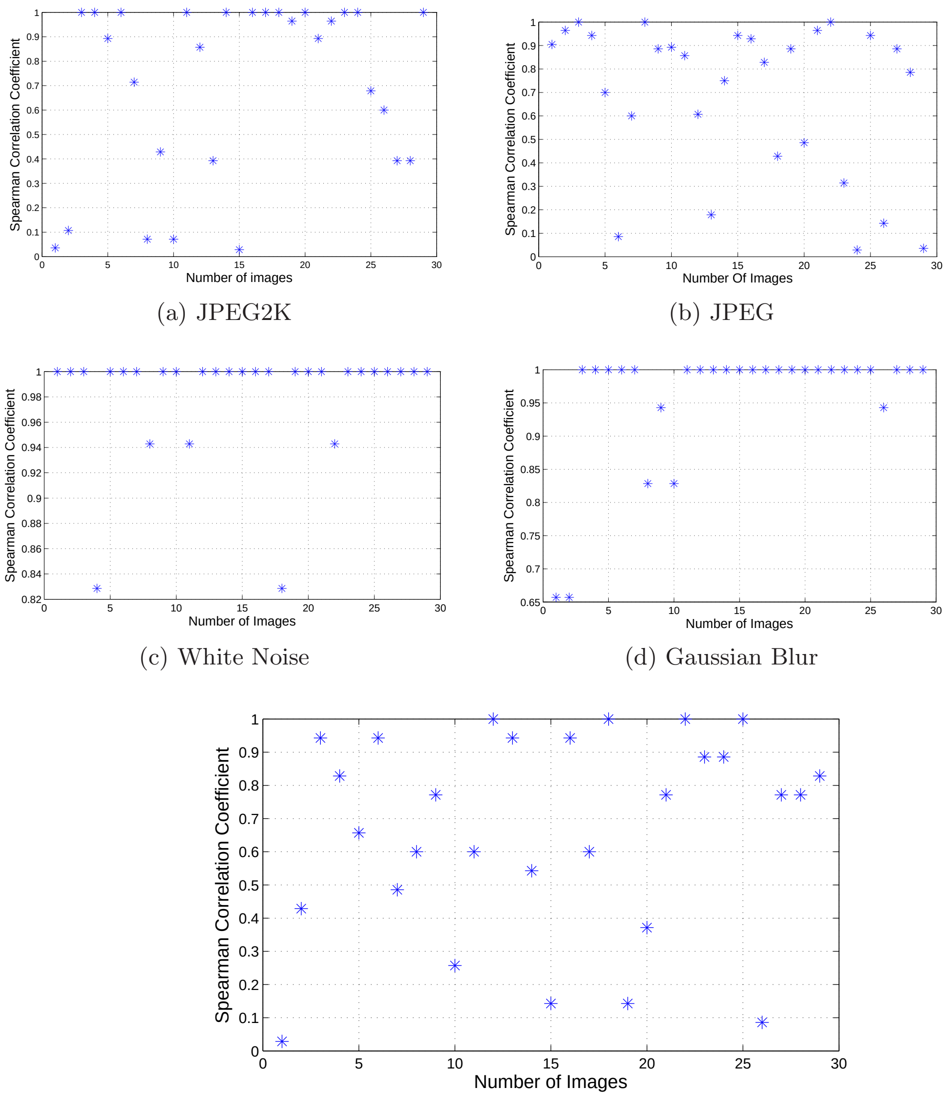
(a) JPEG2K (b) JPEG

(c) White noise (d) Gaussian Blur

(e) Fast Fading

Figure 4.1: Pearson Correlation Coefficient (LCC) between ABQI and SSIM for different types of degradation on LIVE database

Pearson and Spearman Correlation coefficient are used to measure the closeness between ABQI and SSIM indices. High correlation coefficient indicates



(a) JPEG2K (b) JPEG

(c) White Noise (d) Gaussian Blur

(e) Fast Fading

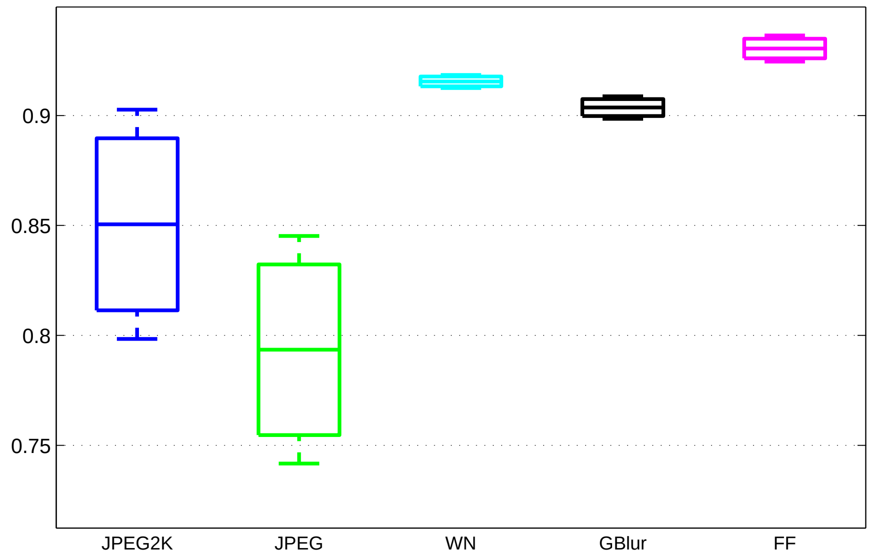
Figure 4.2: Spearman Correlation Coefficient (LCC) between ABQI and SSIM for different types of degradation on LIVE database.

better dependency between the two metrics. So in order to validate the efficacy of the ABQI we had carried out experiment on LIVE database for different type of image distortions.

From Fig.4.1 we can see the Pearson Correlation Coefficient (LCC) calculated between ABQI and SSIM for different types of degradation JPEG2K, JPEG, white noise, Gaussian blur and Fast Fading, on LIVE database.

In scatter plot, the x-axis represents the number of different type of image on which the experiment has been done whereas y-axis represents the correlation coefficient value calculated between ABQI and SSIM scores which are calculated for different type of distortions for each image.

Similarly from Fig.4.2 we can see the Spearman Correlation Coefficient (RCC) calculated between ABQI and SSIM for different types of degradation JPEG2K, JPEG, white noise, Gaussian blur and Fast Fading, on LIVE database.

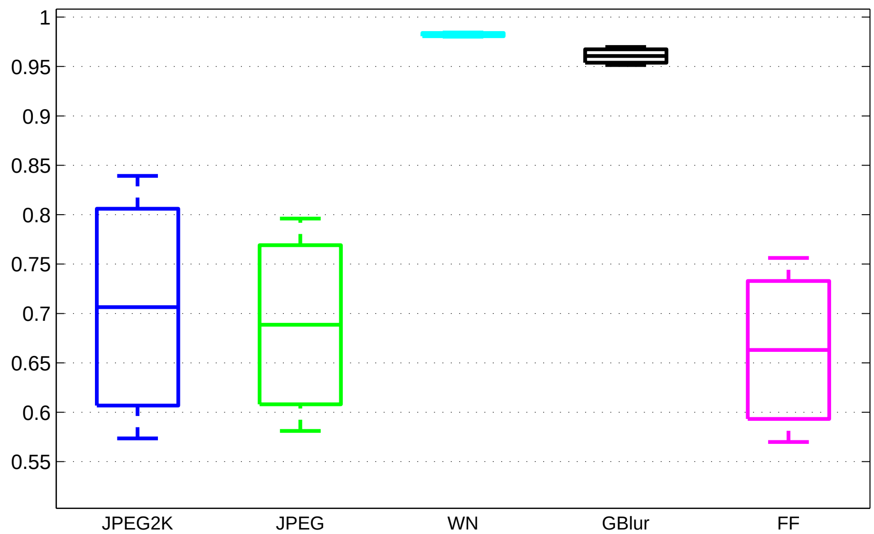


(a)

Figure 4.3: Mean-variance plot for Pearson Correlation Coefficient between ABQI and SSIM for different type of distortions on LIVE database.

X-axis of Fig.4.3 represents five types of distortions used in the LIVE database on which ABQI and SSIM is applied and their Pearson correlation coefficients is calculated. Y-axis represents the mean and variance (spread) of the correlation coefficients calculated from the different type of images from every distortion type. From the box plot it is observed that for fast fading type of distortion have maximum mean of Pearson correlation coefficients but white noise type of distortion have second best mean of Pearson correlation coefficients and have minimum variance (spread). For JPEG type of distortion, it have minimum mean of Pearson correlation coefficients and also have large spread.

Similarly in Fig.4.4 X-axis represents five types of distortions used in the LIVE database on which ABQI and SSIM is applied and their Spearman correlation coefficients is calculated. Y-axis represents the mean and variance



(a)

Figure 4.4: Mean-variance plot for Spearman Correlation Coefficient between ABQI and SSIM for different type of distortions on LIVE database.

(spread) of the correlation coefficients calculated from the different type of images from every distortion type. From the box plot it is observed that for White noise type of distortion have maximum mean of Spearman correlation coefficients and have minimum variance (spread). Gaussian blur type of distortion have second best mean of Spearman correlation coefficients. For JPEG type of distortion, it have minimum mean of Spearman correlation coefficients and also have large spread.

4.4 Discussion

1. All scatter plots for pearson and spearman correlation coefficients calculated for each type of distortion have their value close to 1 for most of the images. Thus showing higher dependency between ABQI and SSIM and hence this validates the efficacy of the ABQI which we had carried out experiment on LIVE database for different type of image distortions.

2. White noise and Gaussian Blur type of distortion had given high mean of correlation coefficients calculated for both Pearson and Spearman and also have very less spread i.e. they give very stable response to the applied

algorithm.

3. However ABQI algorithm is not a suitable choice for assessment of quality if the image is degraded with the following types of distortions: JPEG2K, JPEG or Fast fading (FF).

4. As it is tested on the standard LIVE database it can be concluded that Anisotropic Blind Quality Index algorithm will better perform in white noise and Gaussian blur type of distortions.

4.5 Summary

The chapter describes image database used for the experiment and the results carried out for performance measurement of the developed algorithm. The results obtained were discussed and studied upon.

Chapter 5

Conclusion and Future scope

5.1 Conclusion

S. Gabarda *et al.* [5] argued that ABQI can effectively be used to assess the quality of the image and also compare the performance of this index using peak signal-to-noise ratio (PSNR). However they have not implemented their index on several types of distortions. They have tested the methodology described in their paper with peak signal to noise ratio as the full reference quality metric but PSNR of an image is not a promising metric for quality evaluation [10]. Z. Wang *et al.* [4] considered structural pattern to quantify the similarity between two images, therefore Structural Similarity Index Measure (SSIM) is far better than PSNR when used as an image quality assessment metric. In this thesis we have considered SSIM to measure the performance of ABQI. Thus from the set of experimental results obtained by extensive study on the total of 779 images of the LIVE database, the following points can be concluded -

- As ABQI is highly correlated with SSIM so it can also be considered as a good image quality assessment index for no reference image quality assessment.
- Among the five distortion types (JPEG2K, JPEG, White noise, Gaussian blur and Fast fading) ABQI performs more accurately and give stable performance for White noise and Gaussian blur distortions.

- As calculated correlation coefficients are greater than 0.7 for most of the images studied so ABQI algorithm can be applied on every types of distortions.

5.2 Future scope

This thesis analyses the performance of ABQI on different types of degradations such as additive noise (white noise), JPEG and JPEG2K (generated during compression) and fast fading (generated during transmission). Application of this parameter on multiplicative noise (speckle noise and salt & pepper noise) for the evaluation of its performance is the future scope of this work.

Bibliography

[1] Z. Wang and A. C. Bovik, "Modern image quality assessment," *Synthesis Lectures on Image, Video, and Multimedia Processing*, vol. 2, no. 1, pp. 1–156, 2006.

[2] J. Huang and D. Mumford, "Statistics of natural images and models," in *Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference on.*, vol. 1. IEEE, 1999.

[3] Q. Huynh-Thu and M. Ghanbari, "Scope of validity of psnr in image/video quality assessment," *Electronics letters*, vol. 44, no. 13, pp. 800–801, 2008.

[4] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *Image Processing, IEEE Transactions on*, vol. 13, no. 4, pp. 600–612, 2004.

[5] S. Gabarda and G. Cristóbal, "Blind image quality assessment through anisotropy," *JOSA A*, vol. 24, no. 12, pp. B42–B51, 2007.

[6] T. Claasen and W. Mecklenbrauker, "The wigner distributiona tool for time-frequency signal analysis. part i: Continuous-time signals," *Philips J. Res*, vol. 35, no. 3, pp. 217–250, 1980.

[7] Z. Wang, A. C. Bovik, and L. Lu, "Why is image quality assessment so difficult?" in *Acoustics, Speech, and Signal Processing (ICASSP), 2002 IEEE International Conference on*, vol. 4. IEEE, 2002, pp. IV–3313.

[8] H. Sheikh, Z. Wang, L. Cormack, and A. Bovik, "Live image quality assessment database release 2 (2005)."

[9] M. S. Keil and G. Cristóbal, "Separating the chaff from the wheat: Possible origins of the oblique effect," *JOSA A*, vol. 17, no. 4, pp. 697–710, 2000.

[10] P. Flandrin, R. G. Baraniuk, and O. Michel, "Time-frequency complexity and information," in *Acoustics, Speech, and Signal Processing, 1994. ICASSP-94., 1994 IEEE International Conference on*, vol. 3. IEEE, 1994, pp. III–329.

[11] T.-H. Sang and W. J. Williams, "Renyi information and signal-dependent optimal kernel design," in *Acoustics, Speech, and Signal Processing, 1995. ICASSP-95., 1995 International Conference on*, vol. 2. IEEE, 1995, pp. 997–1000.

[12] L. Stanković, "A measure of some time–frequency distributions concentration," *Signal Processing*, vol. 81, no. 3, pp. 621–631, 2001.

[13] L. D. Jacobson and H. Wechsler, "Joint spatial/spatial-frequency representation," *Signal processing*, vol. 14, no. 1, pp. 37–68, 1988.

[14] J. Lee Rodgers and W. A. Nicewander, "Thirteen ways to look at the correlation coefficient," *The American Statistician*, vol. 42, no. 1, pp. 59–66, 1988.

[15] N. S. Chok, "Pearson's versus spearman's and kendall's correlation coefficients for continuous data," Ph.D. dissertation, University of Pittsburgh, 2010.

[16] S. L. Weinberg and S. K. Abramowitz, *Data analysis for the behavioral sciences using SPSS*. Cambridge University Press, 2002.